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THE STATE OF THE ART AND THE STATE OF THE PRACTICE

TOPIC: C2 Modeling and Simulation

Modeling Supervisory Control and Team Performance in the Air Defense Warfare Domain with Queueing Theory Part II

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Abstract

In our previous research, we hypothesize that the performance of a supervisory control operator that must process tasks recommended by a system task manager is analogous to the performance of a vacationing server, $M/E_r/1$ queue. Thus, we assume that the arrival of tasks is Markovian and that service consists of r- stages of processing each of which is exponentially distributed. In addition, we assume that when there are no tasks in the queue to process, the operator "takes a vacation," i.e., goes off and performs other duties. The model assumed vacation time was exponentially distributed. We derived the queueing statistics for this system. These statistics include (1) the average number of customers (tasks) in the queue, (2) the average time a task spends in the queue, and (3) the average waiting time in the queue. We extended this model to a two-class priority $M/E_r/1$ vacationing server system. The results of these predictions were compared to actual operator performance. Our current research generalizes the arrival processes. That is, instead of assuming that the arrival of tasks follows a Poisson process, we assume a Markov-Modulated Poisson Process (MMPP). The MMPP allows for a change in the rate in which tasks arrive to the system. Thus, "rush hour" effects and the ebb and flow of task arrivals may be taken into account by the new model. In the Command and Control environment, it is particularly important to estimate the "rush hour " effect on time critical events. A new set of queueing statistics was generated for a two-class MMPP/M/1 vacationing server system. This allowed us to compare the model to operator performance on the test scenario over extended periods of time.

Approach

The goal of our research program is to develop quantitative models of operator and system performance that will form the basis of a scientific design approach that can be utilized by Combat System Design Engineers. Our approach demonstrates how operator workload may be quantified so that manning requirements may be specified for future Naval Combat Systems.

The increased automation of combat weapon systems is radically changing the role of the human operator from that of controller to supervisor. As a supervisor, the operator is responsible for monitoring and performing multiple tasks. To support the multitasking activity associated with supervisory control, a Task Manager (TM) display is being incorporated into future combat weapon systems such as the Multimodal Watchstation (MMWS) and the Land Attack Combat System (LACS) (see Osga et al., 2002). The TM display represents tasks, in the form of icons on a display screen, that the system has determined actionable given the current tactical information and Rules of Engagement (ROE). The posting of tasks to the TM display for operators to perform is analogous to service calls arriving at a Help Desk or calls to any telephone system. Other examples include "jobs" arriving at a computer processing system and customers waiting in line for service, such as at a bank, a post office, or grocery checkout counter. In supervisory control, we are interested in the flow of tasks (work) through a system that is composed of both human servers and automated servers (computers). Quantitative models and methods that analyze dynamic systems of flow have been developed in the domain of queuing theory (Kleinrock 1975 & 1976; Takagi, 1991).

We have demonstrated (DiVita, Morris & Osga, 2005; DiVita, Morris & Osga, 2004) that the performance of a supervisory control operator that must process tasks recommended by a

system task manager is analogous to the performance of a vacationing server, $M/E_r/1$ queue. Thus, we assumed that the input process was Markovian and that service consisted of r- stages of processing each of which was exponentially distributed (Erlangian r-stage, E_r). In addition, we assumed that when there were no tasks in the queue to process, the operator "took a vacation," i.e., performed other duties. The model assumed vacation time was exponentially distributed. We derived the queueing statistics for this system. These statistics included (1) the average number of customers (tasks) in the queue- N, (2) the average time a task spent in the queue - T, and (3) the average waiting time in the queue -W. We extended this model to a two-class priority $M/E_r/1$ vacationing server system. The results of these predictions were compared to actual operator performance over the first 33 minutes of an air defense warfare (ADW) scenario entitled the Sea of Japan test scenario.

Data from an air defense warfare (ADW) team consisting of four operators were collected from a one hour and forty-five minute ADW scenario entitled the Sea of Japan (SOJ). Data from this scenario were analyzed from the viewpoint of queueing theory. In Table 1 we compare the queueing model predictions with actual data from the Team 1 Air Warfare Coordinator (AWC) over the first 33 minutes of the scenario. This time period was selected because the arrival rate of tasks did not change over this portion of the scenario.

Table 1: M/Er/1 Priority Queueing model prediction compared to observed AWC data for first change point interval [0, 1995.1].

$\lambda_1 = 1/332.52$ $\lambda_2 = 1/48.66$ $\mu_1 = 1/16.72$ $\mu_2 = 1/16.79$ $V = 1/17.73$	**N_1** ***Mean number of Class 1 tasks in system***	**N_2** ***Mean number of Class 2 tasks in system***	**N** ***Mean number of tasks in system***	**T_1** ***Mean total time for Class 1 tasks in system***	**T_2** ***Mean total time for Class 2 tasks in system***	**T** ***Mean total time for a task in system***	**W_1** ***Mean waiting time for Class 1 tasks***	**W_2** ***Mean waiting time for Class 2 tasks***	**W** ***Mean waiting time for a task.***
Predicted	0.096	0.867	0.964	32.077	42.198	40.906	15.362	25.406	24.124
Observed	0.098	0.787	0.884	32.467	39.602	38.651	15.752	22.496	21.616
% Error	1.22	9.28	8.23	1.22	6.15	5.51	2.54	11.45	10.39

The service time to perform tasks was modeled with a r-stage Erlangian distribution. The number of stages was varied to find the best fit between the second moment of the observed data and the expected second moment of the theorized distribution of service times. This optimal value of r was discovered to be 6.

The vacation time was computed as follows: A *vacation period* is defined as starting when a task is completed and there are no more tasks in the queue to perform. A vacation period ends when the operator returns from vacation and resumes performing tasks. Vacation times are determined by subtracting the first arrival time of a task during each vacation period from the end time of that vacation period. By assuming that the distribution of vacation times is exponentially distributed, the "memoryless" property of the exponential allows us to claim that the mean vacation time may be estimated by the average of the vacation times (V = 17.73 seconds).

Generalizing the Arrival Process

During the course of a scenario, the rate at which tasks appear on the TM display may vary. In general, there are busy periods followed by relatively non-busy periods. This arrival process creates a challenge for queueing theory predictions since, tasks "back-up" during periods of high task flow, but then are completed as the flow of tasks subsides. The impact on performance to time critical events in the context of periods of high and low workload is of particular interest in a command and control situation. Evaluating the manning requirements of combat workstations must take into account the change in workflow. During periods of low workload the system may be over-staffed, but during periods of high workload the system runs the risk of being under-staffed. The Markov-modulated Poisson Process (MMPP) (see Hock, 1996 Chapter 8) may capture the ebb and flow of the task arrivals and its impact on the performance of a queueing system. The MMPP is a doubly stochastic process. In our example, the length of the two periods, rush hour and non-rush hour, randomly varies. This leads to a 2x2 transition rate matrix, Q, where the entries r_i represent the rates at which the underling stochastic process changes. For example, r_1 may represent the rate at which the arrival process changes from non-rush hour to rush hour. In general, q_{ij} represents the rate at which the process changes from state i, to j. q_{ii}, represents the rate at which the process does not change and is set equal to $q_{ii} = -\sum_{j=1, j\neq i}^{m} q_{ij}$ where m is the number of states of the process. In our example, there are only two states, thus:

$$Q = \begin{bmatrix} -r_1 & r_1 \\ r_2 & -r_2 \end{bmatrix}$$

For each state, there is associated a Poisson arrival process with arrival rates $\lambda_{i.}$ In our example there is a λ_1 and λ_2 associated with the rush hour arrival rate and the non-rush hour arrival rate. From these λ's the matrix Λ is created:

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

Letting X_k equal the time between the (k-1) and k^{th} arrival and J_k the state of the Markov process at the time of the k^{th} arrival, then it may be shown that the transition probability distribution matrix, F(x), is given by:

$$F(x) = \{I - \exp((Q - \Lambda)x)\}(\Lambda - Q)^{-1}\Lambda$$

where I is the identity matrix and Q and Λ are the matrices described above. The elements of the matrix $F_{ij}(x)$ represent the conditional probabilities:

$$F_{ij}(x) = P\{J_k = j, X_k \le x \mid J_{k-1} = i)$$

Thus $F_{ij}(x)$ represents the probability that the inter-arrival time between the k and k-1 arrival is less than or equal to x, given that that underlying process was in state i for the k-1 arrival and now is in state j for the k^{th} arrival. The transition probability matrix may be derived by differentiating F(x). Thus:

$$f(x) = \frac{d}{dx} F(x) = e^{\{Q-\Lambda)x} \Lambda$$

Taking the Laplace transform of f(x) we obtain:

$$L[f(x)] = (sI - Q + \Lambda)^{-1} \Lambda$$

In matrix notation we have:

$$L\{f(x)] = \left[\begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix} - \begin{bmatrix} -r_1 & r_1 \\ r_2 & -r_2 \end{bmatrix} + \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}\right]^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$$= \frac{1}{\det A} \begin{bmatrix} (s + r_2 + \lambda_2)\lambda_1 & \lambda_2 r_1 \\ \lambda_1 r_2 & (s + r_1 + \lambda_1)\lambda_2 \end{bmatrix}$$

Where det A = $(s+r_1+\lambda_1)(s+r_2+\lambda_2)-r_1r_2$.

Thus the Laplace transform of the unconditional inter-arrival times is:

$$L[X] = \varphi\left(\frac{1}{\det A} \begin{bmatrix} (s + r_2 + \lambda_2)\lambda_1 & \lambda_2 r_1 \\ \lambda_1 r_2 & (s + r_1 + \lambda_1)\lambda_2 \end{bmatrix}\right) \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$= \frac{s(r_1\lambda_2^2 + r_2\lambda_1^2) + (r_1\lambda_2 + r_2\lambda_1)(r_1\lambda_2 + \lambda_1\lambda_2 + r_2\lambda_1)}{(r_1\lambda_2 + r_2\lambda_1)(s^2 + r_1 + r_2 + \lambda_1 + \lambda_2)(r_1\lambda_2 + \lambda_1\lambda_2 + r_2\lambda_1)}$$

It may be shown that the Laplacian transform for the probability density function (pdf) of inter-arrival times for a generalized arrival function, A(x), must satisfy the equation:

$$\sigma = A^*(m\mu - m\mu\sigma)$$

Where, A*( ) is the Laplacian of the arrival function, A, evaluated at s = $m\mu$-$m\mu\sigma$, m is the number of servers, and σ is the limit of the ratio of the number of times we find the system in state E_{k+1} to the number of times we find the system in the state E_k. The state E_k signifies a new arrival to the queue finding k customers in the queue. Since in our case m =1, we set σ equal to L[X] and substitute μ-$\mu\sigma$ for s in the right-hand-side of the equation for L[X] and then we solve

for σ. In the above 2 x 2 example, we are left with solving a cubic equation and must chose the value of σ that is less than 1. The purpose of deriving this σ is that the waiting time, W, for a generalized arrival process may be expressed in terms of this σ, that is:

$$W = \frac{\sigma}{\mu(1-\sigma)}$$

From W, the average waiting time, T, may easily be determined. In order to determine the average number of customers, N, in the queue, we apply Little's Theorem, where λ is derived to be:

$$\lambda = \frac{\lambda_1 r_2 + \lambda_2 r_1}{r_1 + r_2}$$

Thus a set of queueing statistics may be derived for the MMPP/M/1 queue.

Results

In Figure 1, the running average of the arrival rate of tasks is presented. A change point analysis (Chen & Gupta, 2000) was calculated on the inter-arrival times of tasks to determine changes in the arrival rate. This analysis revealed 3 periods of relatively heavy task flow that lasted, 524.1 sec (8.73 min), 375.7 sec (6.26 min), 376.6 sec (6.28 min). During these periods, the average inter-arrival time of tasks was 15.4 sec, 20.9 sec, and 16.4 sec. Likewise, there were 3 slow periods that lasted 1995.1 sec (33.25 min), 1381.3 sec (23.02 min), and 1656.9 sec (27.62 min). The average inter-arrival time for tasks during these periods was 42.4 sec, 125.6 sec and 61.4 sec. From the inter-arrival times, the average rate of task arrivals, λ_1 and λ_2, can be computed for the slow and busy periods. We assumed that task arrival during these periods was Poisson (with different rates). The average durations for these periods were also assumed to be exponentially distributed. r_1 and r_2 represent the average time spent in low and high activity period, respectively.

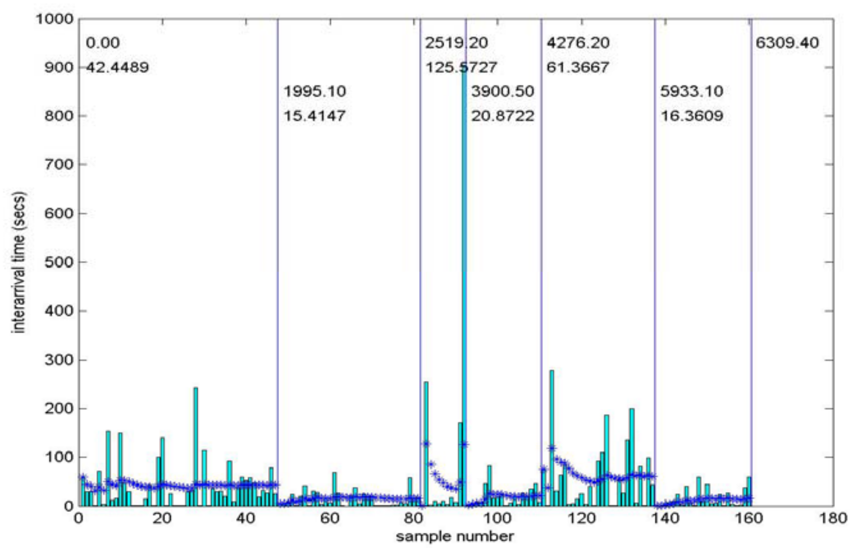

Figure 1: Change point analysis based on the inter-arrival time between AWC tasks for the entire scenario [0, 6309.4]. Asterisks represent the running average.

In Table 2, the results of the M/M/1 queueing predictions are compared to the actual data for the Team 1 AWC operator for the entire scenario. The server was assumed to vacationing. The percent error runs in the 15% - 25% range for the three key statistics – mean number in the system -N, mean total time -T, and mean waiting time in the system -W. Task prioritization was removed from this analysis. The M/M/1 underestimates these statistics. This is because the M/M/1 cannot handle the way in which the tasks pile-up during a burst of rush hour activity.

$\lambda = 1/39.43$ $\mu = 1/17.50$ $V = 1/17.73$	**N** ***Mean number of tasks in the system***	**T** ***Mean total time for a task in the system***	**W** ***Mean waiting time for a task.***
Predicted	1.247	49.190	31.690
Observed	1.443	57.256	39.708
% Error	15.67	16.40	25.30

Table 2: M/M/1 Queueing model prediction compared to observed AWC data for the entire scenario [0, 6309.4], λ represents overall λ.

In Table 3, the results of the MMPP/M/1 queueing predictions are compared to the actual data. The server was assumed to be vacationing. The percent error between observed and predicted data now drops down to the 4%- 8% range, and the effect on performance due to the ebb and flow task arrival rate is better predicted.

$\lambda_1 = 1/59.22$ $\lambda_2 = 1/17.01$ $r_1 = 1/1677.77$ $r_2 = 1/425.37$ $\mu = 1/17.50$ $V = 1/17.73$	**N** ***Mean number of tasks in the system***	**T** ***Mean total time for a task in the system***	**W** ***Mean waiting time for a task.***
Predicted	1.376	54.245	36.745
Observed	1.443	57.256	39.708
% Error	4.89	5.55	8.06

Table 3: Two state MMPP/M/1 Queueing model predictions compared to observed AWC data for the entire scenario [0, 6309.4].

The MMPP may also be used to handle correlated arrivals of tasks. For example, in our test there were a total of 4 operators that made up the ADW team. In the course of the scenario

we observed correlations between tasks that appeared on the Task Manager display, that is, tasks arriving from “outside” the queueing network, and tasks passed between operators – task arriving from “inside” the network. Unfortunately, the total number of tasks for the auxiliary operators was rather small. (The AWC was the main “player” in this scenario). In order to aid our modeling we simulated task arrival and the passing of tasks between operators. Completion rates of tasks was also simulated. In Table 4 we present the results of comparing the predictions for an M/M/1 queue to that of a Matlab simulation of 100,000 tasks presented to the Information Quality Control-1

$\lambda_{outside} = \lambda_{inside} = 1/152.4$ $\mu = 1/15.0$ $V = 1/13.3$	**N** ***Mean number of tasks in the system***	**T** ***Mean total time for a task in the system***	**W** ***Mean waiting time for a task***
Predicted Queueing	0.420	31.976	16.976
Observed IQC1	0.455	34.464	19.430
% Error	8.41	7.78	14.45

Table 4: M/M/1 Queueing model predictions compared to observed IQC1 correlated arrival simulation.

Operator (IQC1) in our queueing network. As can be seen, the predictions are rather poor considering the large number of trials. This is because, in addition to tasks presented on the TM display for the IQC1 (“outside tasks”), he is also passed tasks to do from the AWC (“inside tasks”). There is correlation between the outside tasks appearing on the TM display and the inside passed tasks that causes the tasks to “pile-up” in a manner analogous to the rush hour effect demonstrated in Tables 2 and 3. In order to handle this arrival process an MMPP was applied to the data and the results are listed in Table 5. The MMPP model handles the correlation among the arriving task as is demonstrated by the models accurate predictions.

$\lambda_{outside} = \lambda_{inside} = 1/152.4$ $\mu = 1/15.0$ $V = 1/13.3$	**N** ***Mean number of tasks in the system***	**T** ***Mean total time for a task in the system***	**W** ***Mean waiting time for a task***
Predicted Queueing	0.455	34.478	19.478
Observed IQC1	0.455	34.464	19.430
% Error	0.03	0.04	0.25

Table 5: MMPP/M/1 Queueing model predictions compared to observed IQC1 correlated arrival simulation.

Conclusion

The Markov-Modulated Poisson process (MMPP) generalizes the arrival process of tasks to the operator. In this manner, the slow down in through put can be effectively measured when

a burst of tasks arrive that require the operator to take action. The MMPP/M/1 vacationing server predicts operator performance better than the simpler M/M/1 vacationing server under conditions where task flow varies. This predictive capability is vital to predicting performance to time critical tasks in CIC workstations.

Future research will focus on the following topics: 1) the MMPP models can be extended to handle task priority. 2) the service process may be generalized to be Erlangian, thus predictions for a MMPP/Er/1 need to be generated, 3) the probability distribution of the time a critical task may spend in the system due to a back-log of tasks awaiting service may be calculated. These estimates may then be evaluated by system experts to see if they fall within an acceptable range.

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Modeling Supervisory Control in the Air Defense Warfare Domain with Queueing Theory, Part II[1]

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Decision Support Systems and Models for Intelligent Mission Management

Background

•Multi-mission, multi-tasking, optimally manned CICs will require greater reliance on automation.

•Operators will require resource management tools and planning aids to meet mission requirements - these ***must*** reduce workload in the planning and execution process

GOALS

1. **Model** individual operator and team performance.
2. **Simulate** and quantify the effects of increasing and decreasing team size providing a model of manning and automation requirements.
3. **Test** the nature of task allocation and dynamic task reallocation schemes among team members and autonomous agents.
4. Develop methods to dynamically predict team performance.
5. Develop displays to depict actual team performance dynamically to team leaders and methods to recommend changes towards optimization.
6. Discover behavioral results of team performance awareness with regard to team self-monitoring and correction.

Purpose of Modeling

- Predict impact of design on human performance - before system is built.
- Compare alternative designs.
- Compare alternative job structures, positions, team definitions.
- Predict and compare performance results for design reference missions.
- Reduce design risk.
- Identify design changes and corrections before costly mistakes made.

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Modeling Approaches

1. **GOMSL Modeling (Micro):**

   - Explicitly represents the strategies an individual operator and teams of operators may use to perform tasks.
   - Quantifies operator performance based on these strategies.

2. **Queueing Modeling (Macro):**

   - Quantifies large-scale aspects of system performance: **workload, input, output and work throughput**
   - Represents dynamic **flow of tasks** among a team of operators.
   - These statistics represent **emergent characteristics** of a system that are not directly modeled by GOMSL.

Queueing Theory and Supervisory Control

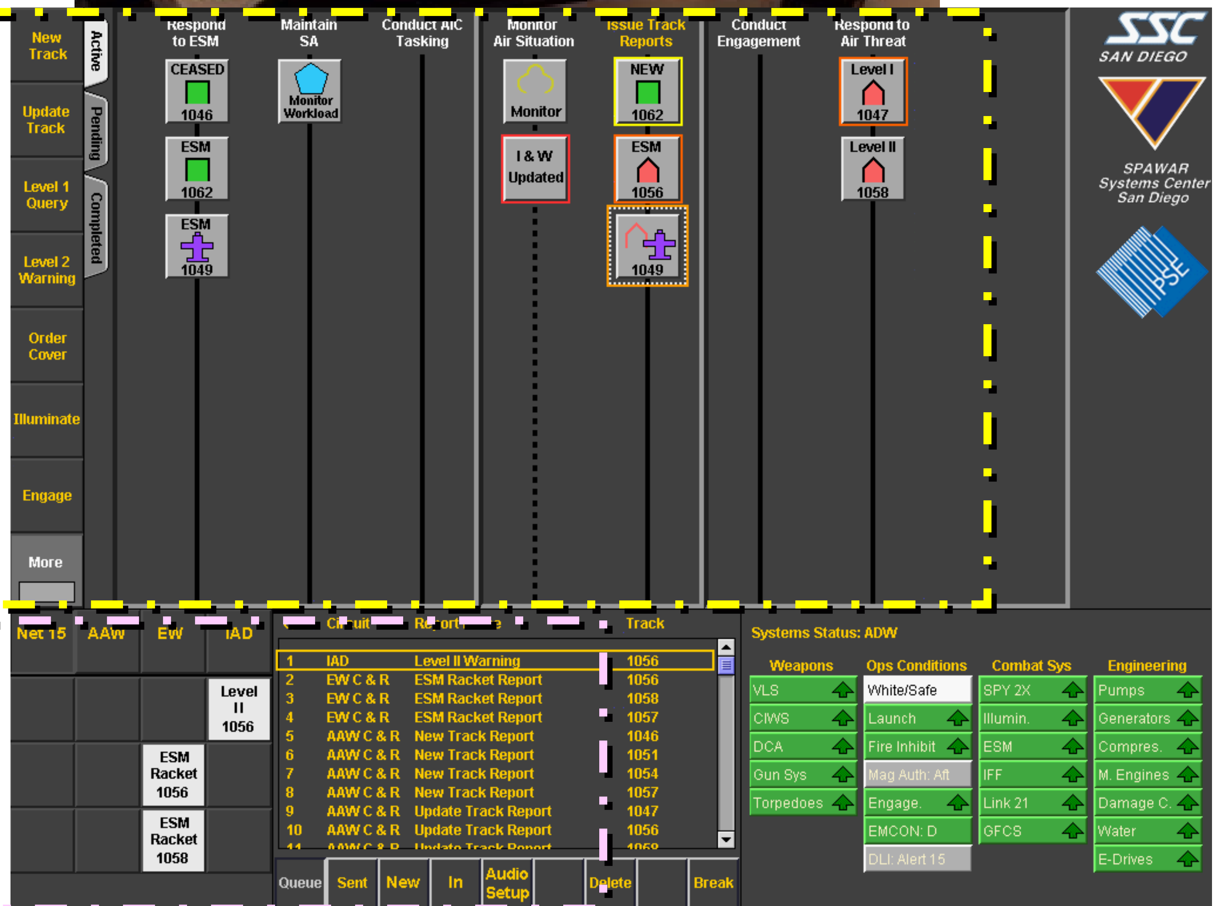
- **Multimodal Watchstation (MMWS)**
- **Land Attack Weapons Systems (LAWCS)**

The increased automation of combat weapon systems is changing the role of the **human operator** from that of **controller to supervisor**.

As a supervisor, the operator is responsible for monitoring and performing **multiple tasks.**

Task Manager Display Supports multitasking activity associated with **supervisory control.**

Task Manager & Status Display

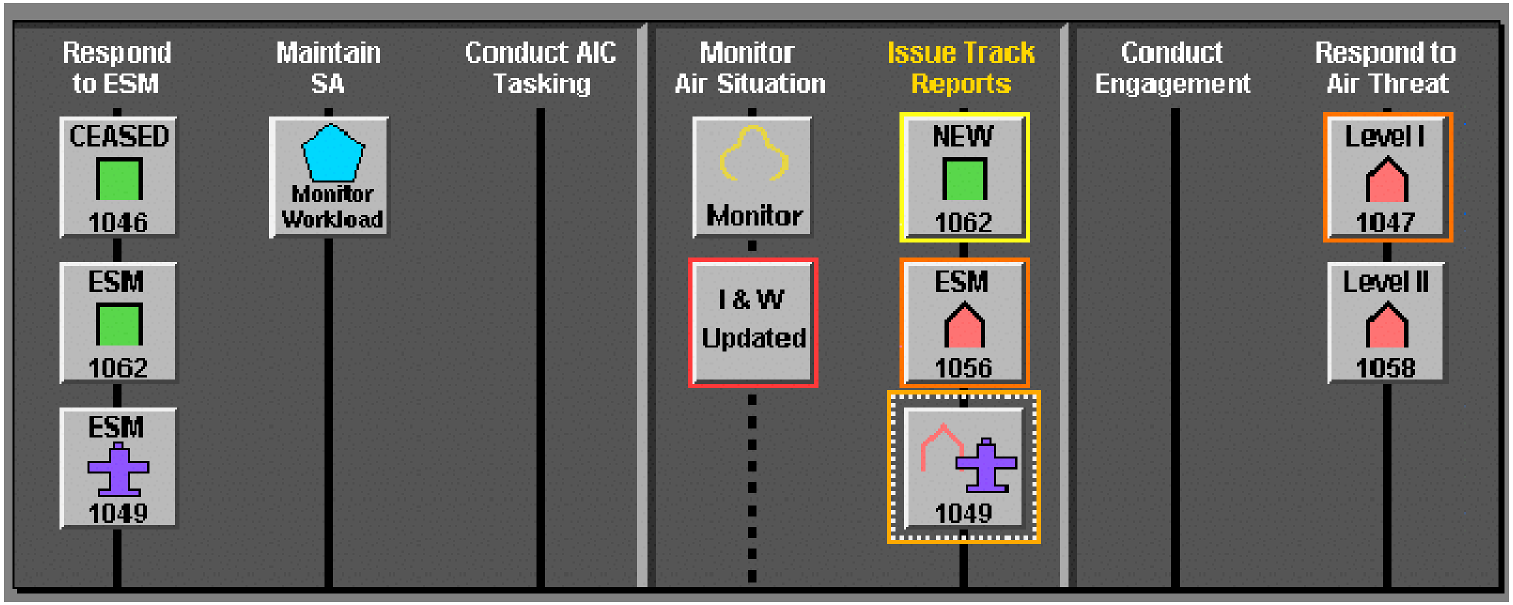


Task Manager Task Queue

Communications

Systems Status

Air Defense Warfare Task Monitoring



Representation of work in terms of tasks servers as a trace - enables designers to track workload and flow of tasks among team members.

Posting of Task analogous to customers arriving at a queue for service: Model Teams with Queueing Theory and Queueing Networks.

Network Queueing Model of Team 1 Task Flow.

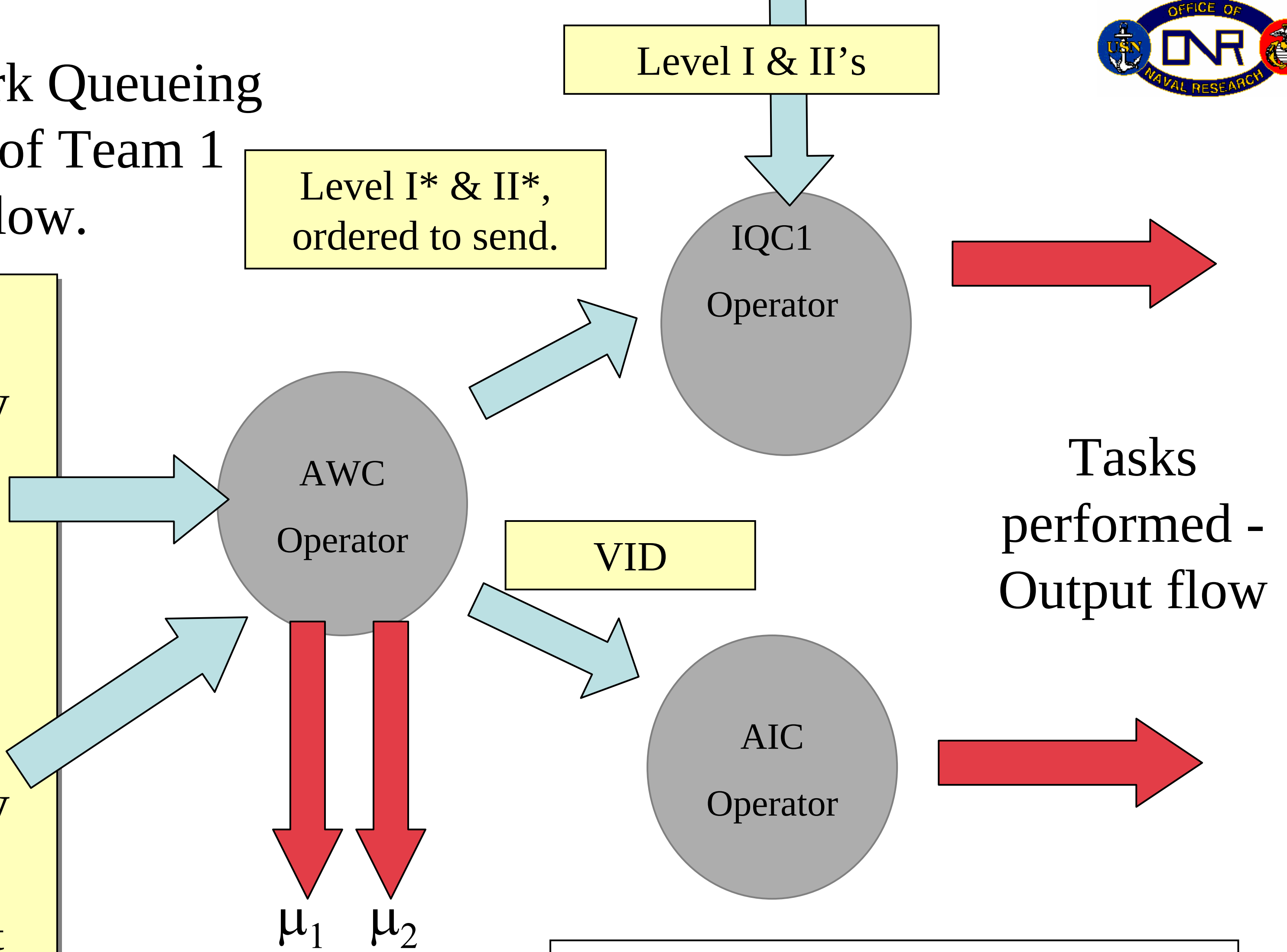
Tasks Entering:

λ_1 High Priority

Level I Query
Level II Warning
VID
Cover
Engage
Illuminate

λ_2 Low Priority

New track Report
Update track Report



Tasks performed - Output Flow

AWC = Air Warfare Coordinator
IQC = Information Quality Control
AIC = Air Intercept Controller

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Components of Queueing Model

1. **The Input or Arrival Process**
2. **The Service Mechanism**
3. **The Queueing Policy**

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Components of Queueing Model

The Input or Arrival Process:

- The **arrival** of customers to a queue is often **unpredictable**, so arrival is modeled as a **random process**.
- The arrival process is often assumed to be **Poisson** in nature where **arrival rate, λ,** is the reciprocal of the mean inter-arrival time of customers.
- For the Poisson distribution with parameter λ, the probability, P_k, that k arrivals occur in the time interval (0,t) is given by:

$$P_k(t) = \frac{(\lambda t)^k}{k!} e^{-\lambda t}$$

Components of Queueing Model

The Service Mechanism:

- Service refers to the **number of "servers"** and the lengths of time the customers hold servers.
- In our case this is the number of operators and the distributions of **reaction times it takes operators to perform various tasks.**
- Service time is modeled by a continuous random variable, x, exponentially distributed with parameter μ :

$$f(x) = \mu e^{-\mu x}$$

Components of Queueing Model

The Service Mechanism:

- **Human reaction time** to various tasks, and task components, are **exponentially distributed** (see Townsend & Ashby, 1984).
- **Service time** may be modeled and shaped. For example, service may be viewed as composed of **several serial stages** each of which is expontentially distributed.
- In this case, an **Erlang distribution** is used to model service time (r represents the number of stages):

$$b(x) = \frac{r\mu(r\mu x)^{r-1} e^{-r\mu x}}{(r-1)!}$$

Components of Queueing Model

The Queueing Policy

- Entails the method by which the system selects customers for service:
  - First-Come-First-Served (FCFS)
  - Last-Come-First-Served (LCFS)
  - Priority
  - Random.

Queueing Policies for this research: **FCFS** and **Priority**

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Vital Statistics of a Queueing System

- The **Load** or **Intensity, ρ,** to a queueing system is defined to be the **ratio** of the rate of **arrivals, λ.** to the rate of **service, μ:**

$$\rho = \frac{\lambda}{\mu}$$

- **Little's Theorem:** The average number of customers to the system, *N,* is equal to the product of the rate of flow of customers, *λ,* and the average time spent in the system, ***T*:**

$$N = \lambda T$$

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OFFICE OF NAVAL RESEARCH

Air Def. Warfare MMWS Experiments

- Four 5-member ADW teams were tested on a 2 hour Scenario - Sea of Japan (SOJ).
- Tactical Action Officer, Air Warfare Coordinator, Information Quality Control (2), Air Intercept Controller.
- Operators were assigned Primary and Secondary Tasks.
- All system recommended tasks were presented on a Task Manager (TM) Display.
- All Teams "self-organized" - were "free" to allocate tasks amongst themselves - not told how or when to reallocate.
- Only support for allocation was visual - listing of tasks on the TM display.

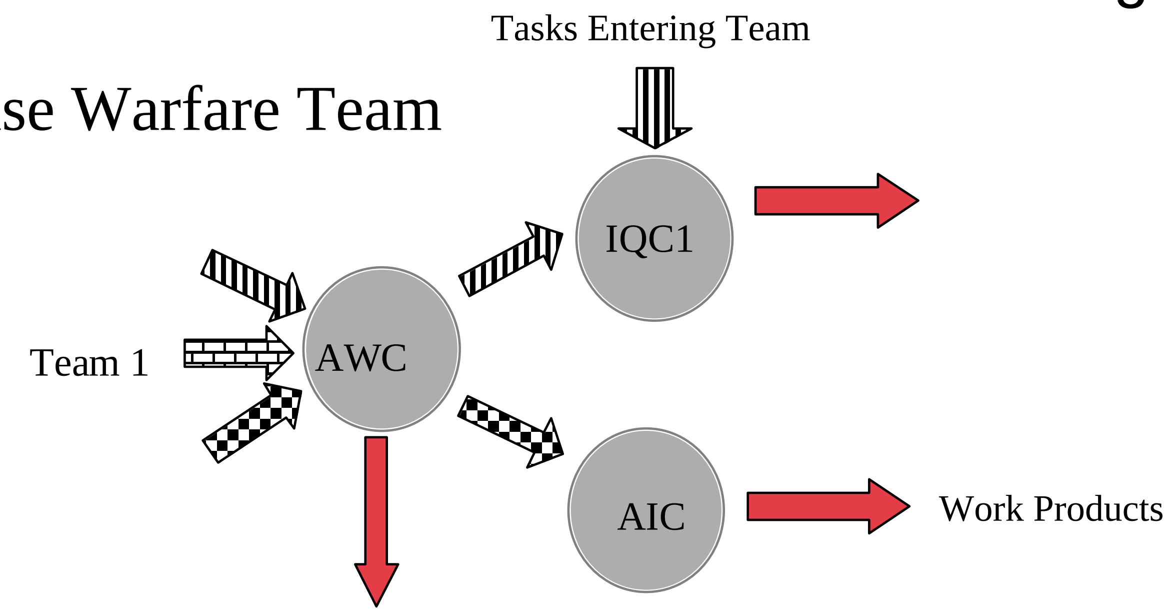
The results provide a basis for building team models.

Results show a contrast between team performance outcomes.

C2 Team Modeling Problem

Problem: The rate at which tasks arrive on the Task Manager display varies - there is a “Rush Hour” Effect - But Rush Hour comes and goes.

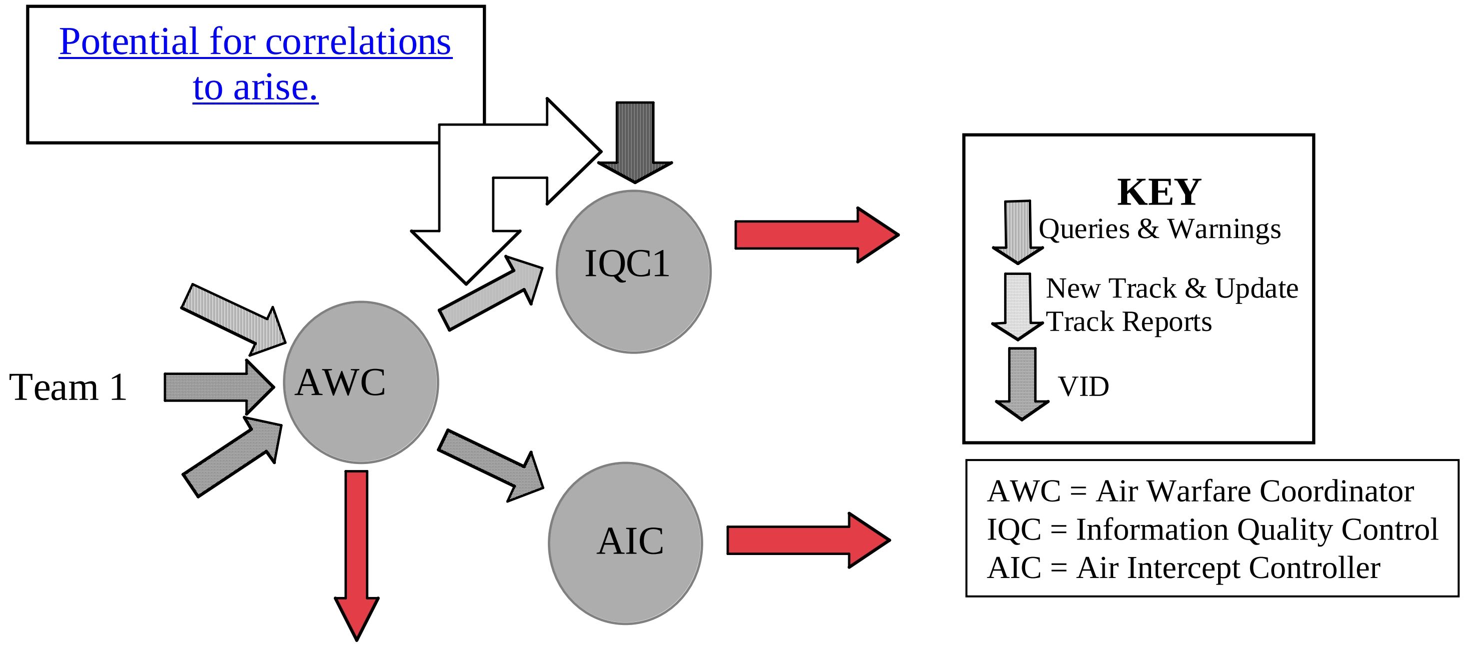
Air-Defense Warfare Team



AWC = Air Warfare Coordinator
IQC = Information Quality Control
AIC = Air Intercept Controller

C2 Team Modeling Problem

PROBLEM: Correlations between arrivals when tasks are passed between operators. Model has to account for these correlations.



Queueing and GOMSL Models

Real-World Issues Affecting Model Accuracy

SPAWAR
Systems Center
San Diego

Arrival Process:
This arrival process creates a challenge for queueing theory predictions since, tasks “back-up” during periods of high task flow, but then are completed as the flow of tasks subsides.

Varying Workload:
The C2 mission impact for performance during time critical events must be addressed within the context of varying periods of high and low workload.

Varying Team Demands:
During periods of low workload the system may be over-staffed, but during periods of high workload the system runs the risk of being under-staffed.

Approach: MMPP Models

The Markov-Modulated Poisson Process (MMPP) captures the ebb and flow of the task arrivals and their impact on the performance of a queueing system.

These are "Doubly Stochastic" Processes:

Two Task Arrival Rates (which are stochastic):

"Rush Hour" & "Non-Rush Hour".

But how long Rush Hour and Non-Rush Hour lasts also varies and is itself stochastic - hence this combination of variable processes is called *doubly stochastic.*

Addressing the Correlation Problem

(Arrival Time Distribution/Service Time Distribution/# of servers)

Using a simplistic **M/M/1** *modeling approach prediction error is high…*

In this Table we present the results of comparing the predictions for an M/M/1 queue to that of a matlab simulation of the Information Quality Control 1 operator (IQC1) in our queueing network. As can be seen, the predictions are rather poor. This is becaus Automation delivered tasks to the IQC1 and the AWC also manually delivered tasks.

$\lambda_{outside} = \lambda_{inside} = 1/152.4$ $\mu = 1/15.0$ $V = 1/13.3$	**N** (average # of tasks)	**T** (average lifetime)	**W** (average lifetime)
Predicted Queueing	0.420	31.976	16.976
Observed IQC1	0.455	34.464	19.430
% Error	8.41	7.78	14.45

Addressing the Correlation Problem

Using The Markov-Modulated Poisson Process (MMPP) % error Is substantially reduced…

$\lambda_{outside} = \lambda_{inside} = 1/152.4$ $\mu = 1/15.0$ $V = 1/13.3$	**N** (average # of tasks)	**T** (average lifetime)	**W** (average lifetime)
Predicted Queueing	0.455	34.478	19.478
Observed IQC1	0.455	34.464	19.430
% Error	0.03	0.04	0.25

Table 9: MMPP/M/1 Queueing model predictions compared to observed IQC1 correlated arrival simulation.

Addressing the Rush Hour Effect…

From $M/E_R/1$ to $MMPP/E_R/1$ Model…

To review: Our previous model handled the first 33 minutes of the Sea of Japan Scenario and incorporated several features:

1. **The Service Time function was generalized to an 6 stage Erlangian.**
2. **The server took "Vacations" when there were no tasks on the Task Manager Display.**
3. **The Tasks were prioritized: high and low.**

$M/E_R/1$ Model Results

λ_1 = 1/332.52 λ_2 = 1/48.66 μ_1 = 1/16.72 μ_2 = 1/16.79 V = 1/17.73	**N_1** *Mean number of Class 1 tasks*	**N_2** *Mean number of Class 2 tasks*	**N** *Mean number of tasks in system*	**T_1** *Mean total time for Class 1 tasks in system*	**T_2** *Mean total time for Class 2 tasks in system*	**T** *Mean total time for a task in system*	**W_1** *Mean waiting time for Class 1 tasks in system*	**W_2** *Mean waiting time for Class 2 tasks in system*	**W** *Mean waiting time for a task in system*
Predicted	0.096	0.867	0.964	32.077	42.198	40.906	15.362	25.406	24.124
Observed	0.098	0.787	0.884	32.467	39.602	38.651	15.752	22.496	21.616
% Error	1.22	9.28	8.23	1.22	6.15	5.51	2.54	11.45	10.39

MMPP/M/1 Model and the Rush Hour Effect

Needed to extend model to entire 1 hour and 45 minute scenario:

Several obstacles first had to be overcome:

1) The data capture didn't specify start and end times of many tasks.

- use estimates of task times derived with GOMSL models and
- viewed hours of time stamped video tapes of the scenario to accurately capture begin and end times.

2) The change in task arrival rate had to be captured.

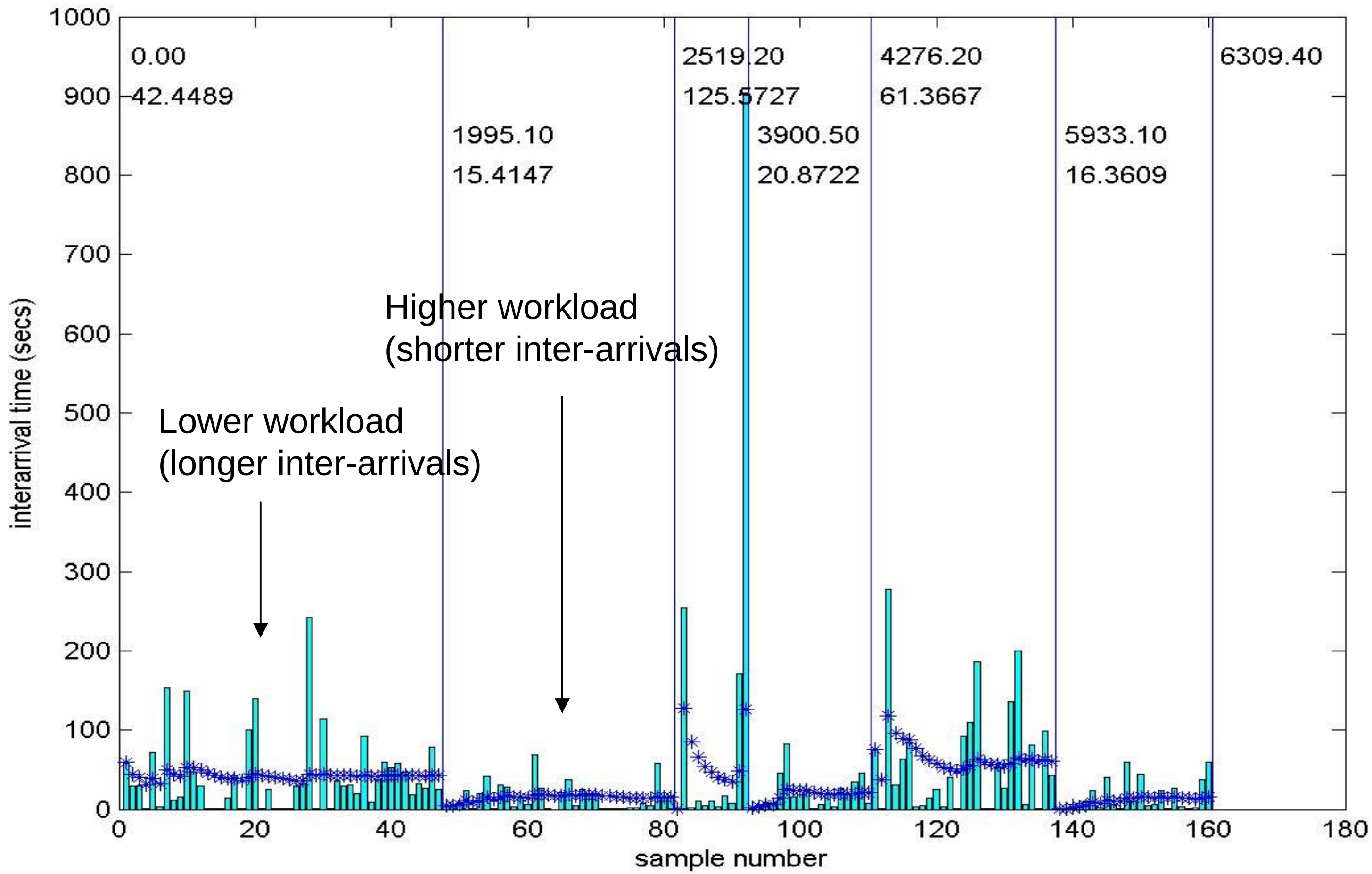
- implement a Change Point Analysis and an entirely different algorithm found in the literature (Meier-Hellerstern).

Both of these Algorithms have their flaws; they give comparable results but not the same answer.

The question: C2 task flow varies but is it best represented with a 2-stage MMPP?

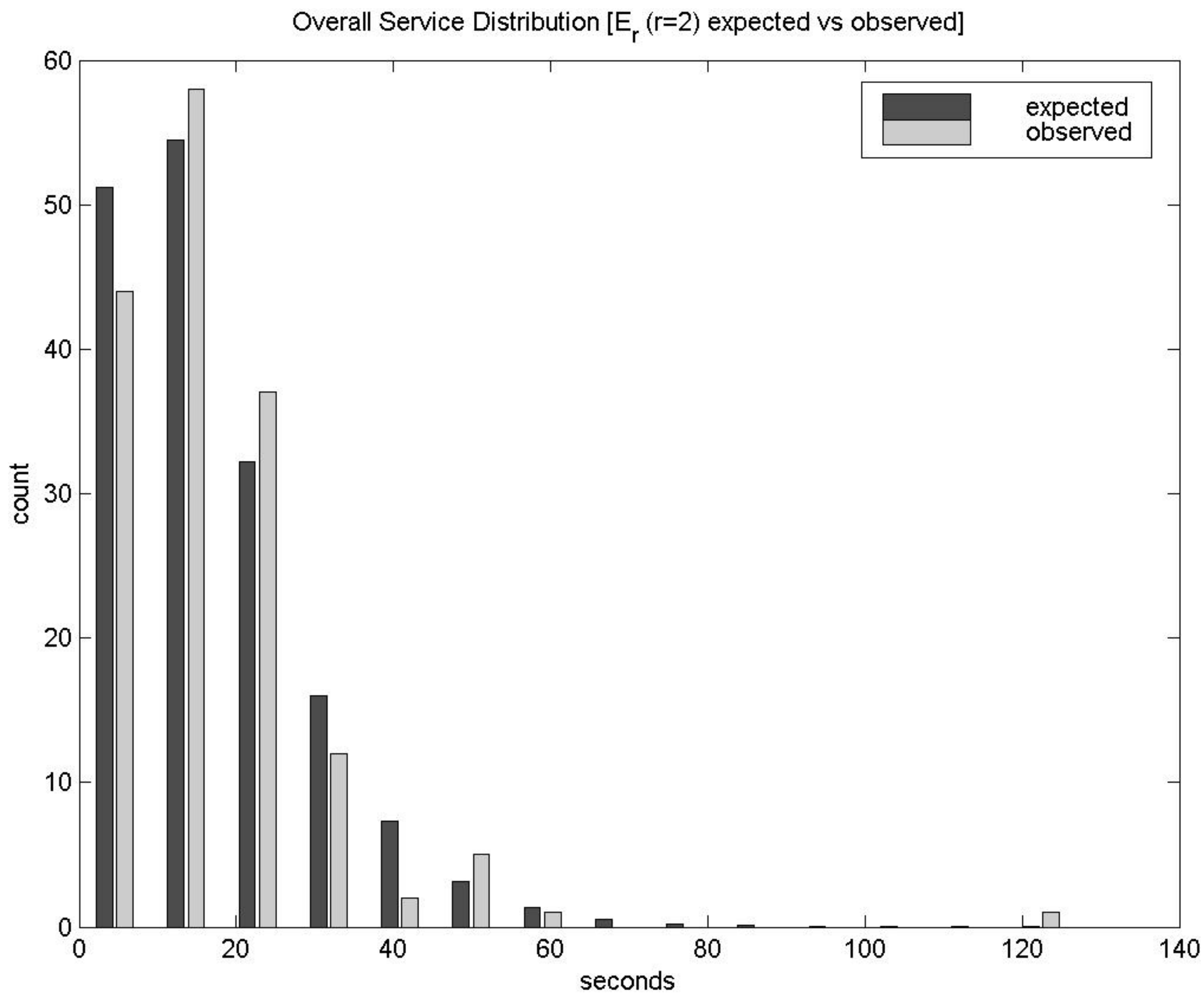
MMPP/M/1 Model and the Rush Hour Effect

Task Inter-arrival times



Change point analysis based on the inter-arrival time between AWC tasks for the entire scenario. Asterisks represent the running average.

Reducing Prediction Error



Erlangian 2-stage service minimizes second moment error - model predictions compared to AWC data for the entire scenario.

Reducing Prediction Error

$1/\lambda_{tot}$: 39.434
$1/\mu$: 17.500
ρ: 0.444

$1/\lambda_1$: 59.215
$1/\lambda_2$: 17.015

$1/r_1$: 1677.767
$1/r_2$: 425.3667

Type	Mean **W**aiting Time of Tasks in System	Mean **N**umber of Tasks in System	Mean **T**otal Time of Task in System
Predict	43.75	1.553	61.250
Observe	39.708	1.443	57.256
Error	4.042	0.110	3.993
% Error	9.239	7.104	6.520

MMPP/E_r/1: 2-state MMPP queueing model predictions (Fischer and Meier-Hellstern, 1992) compared to AWC data for the entire scenario.

Resolving MMPP/M/1 Model Limitations

Issues:

- Need to incorporate generalized service distribution (Done).
- Need to add vacationing server.
- Need to add Prioritization.

We found a discrepancy between our calculated predictions and another algorithm we recently found and implemented from the literature (Fischer and Meier-Hellstern)

The two methods agree only over certain values of the parameters: λ_1, λ_2, r_1, r_2, μ -

This has to be resolved… (FY06 effort)

Conclusions

- Queueing Statistics characterize operator and system performance. Allows for summarization and quantification of system performance.